

XP-002191068

| | |
|----------------|------|
| P.D. 00-00-FN2 | (12) |
| P. 656-666 | |

Chapter 15. Modeling of Data

15.0 Introduction

Given a set of observations, one often wants to condense and summarize the data by fitting it to a "model" that depends on adjustable parameters. Sometimes the model is simply a convenient class of functions, such as polynomials or Gaussians, and the fit supplies the appropriate coefficients. Other times, the model's parameters come from some underlying theory that the data are supposed to satisfy; examples are coefficients of rate equations in a complex network of chemical reactions, or orbital elements of a binary star. Modeling can also be used as a kind of constrained interpolation, where you want to extend a few data points into a continuous function, but with some underlying idea of what that function should look like.

The basic approach in all cases is usually the same: You choose or design a *figure-of-merit function* ("merit function," for short) that measures the agreement between the data and the model with a particular choice of parameters. The merit function is conventionally arranged so that small values represent close agreement. The parameters of the model are then adjusted to achieve a minimum in the merit function, yielding *best-fit parameters*. The adjustment process is thus a problem in minimization in many dimensions. This optimization was the subject of Chapter 10; however, there exist special, more efficient, methods that are specific to modeling, and we will discuss these in this chapter.

There are important issues that go beyond the mere finding of best-fit parameters. Data are generally not exact. They are subject to *measurement errors* (called *noise* in the context of signal-processing). Thus, typical data never exactly fit the model that is being used, even when that model is correct. We need the means to assess whether or not the model is appropriate, that is, we need to test the *goodness-of-fit* against some useful statistical standard.

We usually also need to know the accuracy with which parameters are determined by the data set. In other words, we need to know the likely errors of the best-fit parameters.

Finally, it is not uncommon in fitting data to discover that the merit function is not unimodal, with a single minimum. In some cases, we may be interested in global rather than local questions. Not, "how good is this fit?" but rather, "how sure am I that there is not a *very much better* fit in some corner of parameter space?" As we have seen in Chapter 10, especially §10.9, this kind of problem is generally quite difficult to solve.

The important message we want to deliver is that fitting of parameters is not the end-all of parameter estimation. To be genuinely useful, a fitting procedure

should provide (i) parameters, (ii) error estimates on the parameters, and (iii) a statistical measure of goodness-of-fit. When the third item suggests that the model is an unlikely match to the data, then items (i) and (ii) are probably worthless. Unfortunately, many practitioners of parameter estimation never proceed beyond item (i). They deem a fit acceptable if a graph of data and model "looks good." This approach is known as *chi-by-eye*. Luckily, its practitioners get what they deserve.

CITED REFERENCES AND FURTHER READING:

- Bevington, P.R. 1969, *Data Reduction and Error Analysis for the Physical Sciences* (New York: McGraw-Hill).
- Brownlee, K.A. 1965, *Statistical Theory and Methodology*, 2nd ed. (New York: Wiley).
- Martin, B.R. 1971, *Statistics for Physicists* (New York: Academic Press).
- von Mises, R. 1964, *Mathematical Theory of Probability and Statistics* (New York: Academic Press), Chapter X.
- Korn, G.A., and Korn, T.M. 1968, *Mathematical Handbook for Scientists and Engineers*, 2nd ed. (New York: McGraw-Hill), Chapters 18–19.

15.1 Least Squares as a Maximum Likelihood Estimator

Suppose that we are fitting N data points (x_i, y_i) $i = 1, \dots, N$, to a model that has M adjustable parameters a_j , $j = 1, \dots, M$. The model predicts a functional relationship between the measured independent and dependent variables,

$$y(x) = y(x; a_1 \dots a_M) \quad (15.1.1)$$

where the dependence on the parameters is indicated explicitly on the right-hand side.

What, exactly, do we want to minimize to get fitted values for the a_j 's? The first thing that comes to mind is the familiar least-squares fit,

$$\text{minimize over } a_1 \dots a_M : \sum_{i=1}^N [y_i - y(x_i; a_1 \dots a_M)]^2 \quad (15.1.2)$$

But where does this come from? What general principles is it based on? The answer to these questions takes us into the subject of *maximum likelihood estimators*.

Given a particular data set of x_i 's and y_i 's, we have the intuitive feeling that some parameter sets $a_1 \dots a_M$ are very unlikely — those for which the model function $y(x)$ looks *nothing like* the data — while others may be very likely — those that closely resemble the data. How can we quantify this intuitive feeling? How can we select fitted parameters that are "most likely" to be correct? It is not meaningful to ask the question, "What is the probability that a particular set of fitted parameters $a_1 \dots a_M$ is correct?" The reason is that there is no statistical universe of models from which the parameters are drawn. There is just one model, the correct one, and a statistical universe of data sets that are drawn from it!

That being the case, we can, however, turn the question around, and ask, "Given a particular set of parameters, what is the probability that this data set could have occurred?" If the y_i 's take on continuous values, the probability will always be zero unless we add the phrase, "...plus or minus some fixed Δy on each data point." So let's always take this phrase as understood. If the probability of obtaining the data set is infinitesimally small, then we can conclude that the parameters under consideration are "unlikely" to be right. Conversely, our intuition tells us that the data set should not be too improbable for the correct choice of parameters.

In other words, we identify the probability of the data given the parameters (which is a mathematically computable number), as the *likelihood* of the parameters given the data. This identification is entirely based on intuition. It has no formal mathematical basis in and of itself; as we already remarked, statistics is *not* a branch of mathematics!

Once we make this intuitive identification, however, it is only a small further step to decide to fit for the parameters $a_1 \dots a_M$ precisely by finding those values that *maximize* the likelihood defined in the above way. This form of parameter estimation is *maximum likelihood estimation*.

We are now ready to make the connection to (15.1.2). Suppose that each data point y_i has a measurement error that is independently random and distributed as a normal (Gaussian) distribution around the "true" model $y(x)$. And suppose that the standard deviations σ of these normal distributions are the same for all points. Then the probability of the data set is the product of the probabilities of each point,

$$P \propto \prod_{i=1}^N \left\{ \exp \left[-\frac{1}{2} \left(\frac{y_i - y(x_i)}{\sigma} \right)^2 \right] \Delta y \right\} \quad (15.1.3)$$

Notice that there is a factor Δy in each term in the product. Maximizing (15.1.3) is equivalent to maximizing its logarithm, or minimizing the negative of its logarithm, namely,

$$\left[\sum_{i=1}^N \frac{[y_i - y(x_i)]^2}{2\sigma^2} \right] - N \log \Delta y \quad (15.1.4)$$

Since N , σ , and Δy are all constants, minimizing this equation is equivalent to minimizing (15.1.2).

What we see is that least-squares fitting is a maximum-likelihood estimation of the fitted parameters if the measurement errors are independent and normally distributed with constant standard deviation. Notice that we made no assumption about the linearity or nonlinearity of the model $y(x; a_1 \dots a_M)$ in its parameters $a_1 \dots a_M$. Just below, we will relax our assumption of constant standard deviations and obtain the very similar formulas for what is called "chi-square fitting" or "weighted least-squares fitting." First, however, let us discuss further our very stringent assumption of a normal distribution.

For a hundred years or so, mathematical statisticians have been in love with the fact that the probability distribution of the sum of a very large number of very small random deviations almost always converges to a normal distribution. (For precise statements of this *central limit theorem*, consult [1] or other standard works on mathematical statistics.) This infatuation tended to focus interest away from the

fact that, for real data, the normal distribution is often rather poorly realized, if it is realized at all. We are often taught, rather casually, that, on average, measurements will fall within $\pm\sigma$ of the true value 68 percent of the time, within $\pm 2\sigma$ 95 percent of the time, and within $\pm 3\sigma$ 99.7 percent of the time. Extending this, one would expect a measurement to be off by $\pm 20\sigma$ only one time out of 2×10^{88} . We all know that "glitches" are much more likely than *that*!

In some instances, the deviations from a normal distribution are easy to understand and quantify. For example, in measurements obtained by counting events, the measurement errors are usually distributed as a Poisson distribution, whose cumulative probability function was already discussed in §6.2. When the number of counts going into one data point is large, the Poisson distribution converges towards a Gaussian. However, the convergence is not uniform when measured in fractional accuracy. The more standard deviations out on the tail of the distribution, the larger the number of counts must be before a value close to the Gaussian is realized. The sign of the effect is always the same: The Gaussian predicts that "tail" events are much less likely than they actually (by Poisson) are. This causes such events, when they occur, to skew a least-squares fit much more than they ought.

Other times, the deviations from a normal distribution are not so easy to understand in detail. Experimental points are occasionally just *way off*. Perhaps the power flickered during a point's measurement, or someone kicked the apparatus, or someone wrote down a wrong number. Points like this are called *outliers*. They can easily turn a least-squares fit on otherwise adequate data into nonsense. Their probability of occurrence in the assumed Gaussian model is so small that the maximum likelihood estimator is willing to distort the whole curve to try to bring them, mistakenly, into line.

The subject of *robust statistics* deals with cases where the normal or Gaussian model is a bad approximation, or cases where outliers are important. We will discuss robust methods briefly in §15.7. All the sections between this one and that one assume, one way or the other, a Gaussian model for the measurement errors in the data. It is quite important that you keep the limitations of that model in mind, even as you use the very useful methods that follow from assuming it.

Finally, note that our discussion of measurement errors has been limited to *statistical* errors, the kind that will average away if we only take enough data. Measurements are also susceptible to *systematic* errors that will not go away with any amount of averaging. For example, the calibration of a metal meter stick might depend on its temperature. If we take all our measurements at the same wrong temperature, then no amount of averaging or numerical processing will correct for this unrecognized systematic error.

Chi-Square Fitting

We considered the chi-square statistic once before, in §14.3. Here it arises in a slightly different context.

If each data point (x_i, y_i) has its own, known standard deviation σ_i , then equation (15.1.3) is modified only by putting a subscript i on the symbol σ . That subscript also propagates docilely into (15.1.4), so that the maximum likelihood

estimate of the model parameters is obtained by minimizing the quantity

$$\chi^2 \equiv \sum_{i=1}^N \left(\frac{y_i - y(x_i; a_1 \dots a_M)}{\sigma_i} \right)^2 \quad (15.1.5)$$

called the "chi-square."

To whatever extent the measurement errors actually *are* normally distributed, the quantity χ^2 is correspondingly a sum of N squares of normally distributed quantities, each normalized to unit variance. Once we have adjusted the $a_1 \dots a_M$ to minimize the value of χ^2 , the terms in the sum are not all statistically independent. For models that are linear in the a 's, however, it turns out that the probability distribution for different values of χ^2 at its minimum can nevertheless be derived analytically, and is the *chi-square distribution for $N - M$ degrees of freedom*. We learned how to compute this probability function using the incomplete gamma function `gammap` in §6.2. In particular, equation (6.2.18) gives the probability Q that the chi-square should exceed a particular value χ^2 by chance, where $\nu = N - M$ is the *number of degrees of freedom*. The quantity Q , or its complement $P \equiv 1 - Q$, is frequently tabulated in appendices to statistics books, but we generally find it easier to use `gammap` and compute our own values: $Q = \text{gammap}(0.5\nu, 0.5\chi^2)$. It is quite common, and usually not too wrong, to assume that the chi-square distribution holds even for models that are not strictly linear in the a 's.

This computed probability gives a quantitative measure for the goodness-of-fit of the model. If Q is a very small probability for some particular data set, then the apparent discrepancies are unlikely to be chance fluctuations. Much more probably either (i) the model is wrong — can be statistically rejected, or (ii) someone has lied to you about the size of the measurement errors σ_i — they are really larger than stated.

It is an important point that the chi-square probability Q does not directly measure the credibility of the assumption that the measurement errors are normally distributed. It assumes they are. In most, but not all, cases, however, the effect of nonnormal errors is to create an abundance of outlier points. These decrease the probability Q , so that we can add another possible, though less definitive, conclusion to the above list: (iii) the measurement errors may not be normally distributed.

Possibility (iii) is fairly common, and also fairly benign. It is for this reason that reasonable experimenters are often rather tolerant of low probabilities Q . It is not uncommon to deem acceptable on equal terms any models with, say, $Q > 0.001$. This is not as sloppy as it sounds: Truly *wrong* models will often be rejected with vastly smaller values of Q , 10^{-18} , say. However, if day-in and day-out you find yourself accepting models with $Q \sim 10^{-3}$, you really should track down the cause.

If you happen to know the actual distribution law of your measurement errors, then you might wish to *Monte Carlo simulate* some data sets drawn from a particular model, cf. §7.2–§7.3. You can then subject these synthetic data sets to your actual fitting procedure, so as to determine both the probability distribution of the χ^2 statistic, and also the accuracy with which your model parameters are reproduced by the fit. We discuss this further in §15.6. The technique is very general, but it can also be very expensive.

At the opposite extreme, it sometimes happens that the probability Q is too large, too near to 1, literally too good to be true! Nonnormal measurement errors cannot in general produce this disease, since the normal distribution is about as "compact"

as a distribution can be. Almost always, the cause of too good a chi-square fit is that the experimenter, in a "fit" of conservatism, has *overestimated* his or her measurement errors. Very rarely, too good a chi-square signals actual fraud, data that has been "fudged" to fit the model.

A rule of thumb is that a "typical" value of χ^2 for a "moderately" good fit is $\chi^2 \approx \nu$. More precise is the statement that the χ^2 statistic has a mean ν and a standard deviation $\sqrt{2\nu}$, and, asymptotically for large ν , becomes normally distributed.

In some cases the uncertainties associated with a set of measurements are not known in advance, and considerations related to χ^2 fitting are used to derive a value for σ . If we assume that all measurements have the same standard deviation, $\sigma_i = \sigma$, and that the model does fit well, then we can proceed by first assigning an arbitrary constant σ to all points, next fitting for the model parameters by minimizing χ^2 , and finally recomputing

$$\sigma^2 = \sum_{i=1}^N [y_i - y(x_i)]^2 / (N - M) \quad (15.1.6)$$

Obviously, this approach prohibits an independent assessment of goodness-of-fit, a fact occasionally missed by its adherents. When, however, the measurement error is not known, this approach at least allows *some* kind of error bar to be assigned to the points.

If we take the derivative of equation (15.1.5) with respect to the parameters a_k , we obtain equations that must hold at the chi-square minimum,

$$0 = \sum_{i=1}^N \left(\frac{y_i - y(x_i)}{\sigma_i^2} \right) \left(\frac{\partial y(x_i; \dots a_k \dots)}{\partial a_k} \right) \quad k = 1, \dots, M \quad (15.1.7)$$

Equation (15.1.7) is, in general, a set of M nonlinear equations for the M unknown a_k . Various of the procedures described subsequently in this chapter derive from (15.1.7) and its specializations.

CITED REFERENCES AND FURTHER READING:

- Bevington, P.R. 1969, *Data Reduction and Error Analysis for the Physical Sciences* (New York: McGraw-Hill), Chapters 1-4.
 von Mises, R. 1964, *Mathematical Theory of Probability and Statistics* (New York: Academic Press), §VI.C. [1]

15.2 Fitting Data to a Straight Line

A concrete example will make the considerations of the previous section more meaningful. We consider the problem of fitting a set of N data points (x_i, y_i) to a straight-line model

$$y(x) = y(x; a, b) = a + bx \quad (15.2.1)$$

This problem is often called *linear regression*, a terminology that originated, long ago, in the social sciences. We assume that the uncertainty σ_i associated with each measurement y_i is known, and that the x_i 's (values of the dependent variable) are known exactly.

To measure how well the model agrees with the data, we use the chi-square merit function (15.1.5), which in this case is

$$\chi^2(a, b) = \sum_{i=1}^N \left(\frac{y_i - a - bx_i}{\sigma_i} \right)^2 \quad (15.2.2)$$

If the measurement errors are normally distributed, then this merit function will give maximum likelihood parameter estimations of a and b ; if the errors are not normally distributed, then the estimations are not maximum likelihood, but may still be useful in a practical sense. In §15.7, we will treat the case where outlier points are so numerous as to render the χ^2 merit function useless.

Equation (15.2.2) is minimized to determine a and b . At its minimum, derivatives of $\chi^2(a, b)$ with respect to a, b vanish.

$$\begin{aligned} 0 &= \frac{\partial \chi^2}{\partial a} = -2 \sum_{i=1}^N \frac{y_i - a - bx_i}{\sigma_i^2} \\ 0 &= \frac{\partial \chi^2}{\partial b} = -2 \sum_{i=1}^N \frac{x_i(y_i - a - bx_i)}{\sigma_i^2} \end{aligned} \quad (15.2.3)$$

These conditions can be rewritten in a convenient form if we define the following sums:

$$\begin{aligned} S &\equiv \sum_{i=1}^N \frac{1}{\sigma_i^2} & S_x &\equiv \sum_{i=1}^N \frac{x_i}{\sigma_i^2} & S_y &\equiv \sum_{i=1}^N \frac{y_i}{\sigma_i^2} \\ S_{xx} &\equiv \sum_{i=1}^N \frac{x_i^2}{\sigma_i^2} & S_{xy} &\equiv \sum_{i=1}^N \frac{x_i y_i}{\sigma_i^2} \end{aligned} \quad (15.2.4)$$

With these definitions (15.2.3) becomes

$$\begin{aligned} aS + bS_x &= S_y \\ aS_x + bS_{xx} &= S_{xy} \end{aligned} \quad (15.2.5)$$

The solution of these two equations in two unknowns is calculated as

$$\begin{aligned} \Delta &\equiv SS_{xx} - (S_x)^2 \\ a &= \frac{S_{xx}S_y - S_xS_{xy}}{\Delta} \\ b &= \frac{SS_{xy} - S_xS_y}{\Delta} \end{aligned} \quad (15.2.6)$$

Equation (15.2.6) gives the solution for the best-fit model parameters a and b .

We are not done, however. We must estimate the probable uncertainties in the estimates of a and b , since obviously the measurement errors in the data must introduce some uncertainty in the determination of those parameters. If the data are independent, then each contributes its own bit of uncertainty to the parameters. Consideration of propagation of errors shows that the variance σ_f^2 in the value of any function will be

$$\sigma_f^2 = \sum_{i=1}^N \sigma_i^2 \left(\frac{\partial f}{\partial y_i} \right)^2 \quad (15.2.7)$$

For the straight line, the derivatives of a and b with respect to y_i can be directly evaluated from the solution:

$$\begin{aligned} \frac{\partial a}{\partial y_i} &= \frac{S_{xx} - S_x x_i}{\sigma_i^2 \Delta} \\ \frac{\partial b}{\partial y_i} &= \frac{S x_i - S_x}{\sigma_i^2 \Delta} \end{aligned} \quad (15.2.8)$$

Summing over the points as in (15.2.7), we get

$$\begin{aligned} \sigma_a^2 &= S_{xx} / \Delta \\ \sigma_b^2 &= S / \Delta \end{aligned} \quad (15.2.9)$$

which are the variances in the estimates of a and b , respectively. We will see in §15.6 that an additional number is also needed to characterize properly the probable uncertainty of the parameter estimation. That number is the *covariance* of a and b , and (as we will see below) is given by

$$\text{Cov}(a, b) = -S_x / \Delta \quad (15.2.10)$$

The coefficient of correlation between the uncertainty in a and the uncertainty in b , which is a number between -1 and 1 , follows from (15.2.10) (compare equation 14.5.1),

$$r_{ab} = \frac{-S_x}{\sqrt{S S_{xx}}} \quad (15.2.11)$$

A positive value of r_{ab} indicates that the errors in a and b are likely to have the same sign, while a negative value indicates the errors are anticorrelated, likely to have opposite signs.

We are *still* not done. We must estimate the goodness-of-fit of the data to the model. Absent this estimate, we have not the slightest indication that the parameters a and b in the model have any meaning at all! The probability Q that a value of chi-square as *poor* as the value (15.2.2) should occur by chance is

$$Q = \text{gammap} \left(\frac{N-2}{2}, \frac{\chi^2}{2} \right) \quad (15.2.12)$$

Here `gammq` is our routine for the incomplete gamma function $Q(a, x)$, §6.2. If Q is larger than, say, 0.1, then the goodness-of-fit is believable. If it is larger than, say, 0.001, then the fit *may* be acceptable if the errors are nonnormal or have been moderately underestimated. If Q is less than 0.001 then the model and/or estimation procedure can rightly be called into question. In this latter case, turn to §15.7 to proceed further.

If you do not know the individual measurement errors of the points σ_i , and are proceeding (dangerously) to use equation (15.1.6) for estimating these errors, then here is the procedure for estimating the probable uncertainties of the parameters a and b : Set $\sigma_i \equiv 1$ in all equations through (15.2.6), and multiply σ_a and σ_b , as obtained from equation (15.2.9), by the additional factor $\sqrt{\chi^2/(N-2)}$, where χ^2 is computed by (15.2.2) using the fitted parameters a and b . As discussed above, this procedure is equivalent to *assuming* a good fit, so you get no independent goodness-of-fit probability Q .

In §14.5 we promised a relation between the linear correlation coefficient r (equation 14.5.1) and a goodness-of-fit measure, χ^2 (equation 15.2.2). For unweighted data (all $\sigma_i = 1$), that relation is

$$\chi^2 = (1 - r^2)N\text{Var}(y_1 \dots y_N) \quad (15.2.13)$$

where

$$N\text{Var}(y_1 \dots y_N) \equiv \sum_{i=1}^N (y_i - \bar{y})^2 \quad (15.2.14)$$

For data with varying weights σ_i , the above equations remain valid if the sums in equation (14.5.1) are weighted by $1/\sigma_i^2$.

The following function, `fit`, carries out exactly the operations that we have discussed. When the weights σ are known in advance, the calculations exactly correspond to the formulas above. However, when weights σ are unavailable, the routine *assumes* equal values of σ for each point and *assumes* a good fit, as discussed in §15.1.

The formulas (15.2.6) are susceptible to roundoff error. Accordingly, we rewrite them as follows: Define

$$t_i = \frac{1}{\sigma_i} \left(x_i - \frac{S_x}{S} \right), \quad i = 1, 2, \dots, N \quad (15.2.15)$$

and

$$S_{tt} = \sum_{i=1}^N t_i^2 \quad (15.2.16)$$

Then, as you can verify by direct substitution,

$$b = \frac{1}{S_{tt}} \sum_{i=1}^N \frac{t_i y_i}{\sigma_i} \quad (15.2.17)$$

$$a = \frac{S_y - S_x b}{S} \quad (15.2.18)$$

$$\sigma_a^2 = \frac{1}{S} \left(1 + \frac{S_x^2}{SS_{xx}} \right) \quad (15.2.19)$$

$$\sigma_b^2 = \frac{1}{SS_{xx}} \quad (15.2.20)$$

$$\text{Cov}(a, b) = -\frac{S_x}{SS_{xx}} \quad (15.2.21)$$

$$r_{ab} = \frac{\text{Cov}(a, b)}{\sigma_a \sigma_b} \quad (15.2.22)$$

```

#include <math.h>
#include "nrutil.h"

void fit(float x[], float y[], int ndata, float sig[], int mwt, float *a,
        float *b, float *siga, float *sigb, float *chi2, float *q)
    Given a set of data points x[1..ndata], y[1..ndata] with individual standard deviations
    sig[1..ndata], fit them to a straight line y = a + bx by minimizing  $\chi^2$ . Returned are
    a, b and their respective probable uncertainties siga and sigb, the chi-square chi2, and the
    goodness-of-fit probability q (that the fit would have  $\chi^2$  this large or larger). If mwt=0 on
    input, then the standard deviations are assumed to be unavailable: q is returned as 1.0 and
    the normalization of chi2 is to unit standard deviation on all points.
{
    float gamq(float a, float x);
    int i;
    float wt, t, sxoss, sx=0.0, sy=0.0, st2=0.0, ss, sigdat;

    *b=0.0;
    if (mwt) {
        ss=0.0;
        for (i=1; i<=ndata; i++) {
            wt=1.0/SQR(sig[i]);
            sx += wt*x[i];
            sy += wt*y[i];
            ss += wt;
        }
        // Accumulate sums ...
        // ...with weights
    } else {
        for (i=1; i<=ndata; i++) {
            sx += x[i];
            sy += y[i];
            ss += 1.0;
        }
        // ...or without weights.
    }
    sxoss=sx/ss;
    if (mwt) {
        for (i=1; i<=ndata; i++) {
            t=(x[i]-sxoss)/sig[i];
            st2 += t*t;
            *b += t*y[i]/sig[i];
        }
    } else {
        for (i=1; i<=ndata; i++) {
            t=x[i]-sxoss;
            st2 += t*t;
            *b += t*y[i];
        }
    }
    *a /= st2;
    // Solve for a, b, sigma, and sigma_b.
    *a=(sy-sx*(*b))/ss;
    *siga=sqrt((1.0+sx*sx/(ss*st2))/ss);
    *sigb=sqrt(1.0/st2);
}

```

```

*chi2=0.0;                                Calculate  $\chi^2$ .
if (mvt == 0) {
    for (i=1; i<=ndata; i++)
        *chi2 += SQR(y[i]-(a)-(b)*x[i]);
    *q=1.0;
    sigdat=sqrt(*chi2/(ndata-2));           For unweighted data evaluate typi-
    *siga *= sigdat;                        cal sig using chi2, and adjust
    *sigb *= sigdat;                        the standard deviations.
} else {
    for (i=1; i<=ndata; i++)
        *chi2 += SQR((y[i]-(a)-(b)*x[i])/sig[i]);
    *q=gammq(0.5*(ndata-2), 0.5*(*chi2));   Equation (15.2.12).
}
}

```

CITED REFERENCES AND FURTHER READING:

Bevington, P.R. 1969, *Data Reduction and Error Analysis for the Physical Sciences* (New York: McGraw-Hill), Chapter 6.

15.3 Straight-Line Data with Errors in Both Coordinates

If experimental data are subject to measurement error not only in the y_i 's, but also in the x_i 's, then the task of fitting a straight-line model

$$y(x) = a + bx \quad (15.3.1)$$

is considerably harder. It is straightforward to write down the χ^2 merit function for this case,

$$\chi^2(a, b) = \sum_{i=1}^N \frac{(y_i - a - bx_i)^2}{\sigma_{y_i}^2 + b^2 \sigma_{x_i}^2} \quad (15.3.2)$$

where σ_{x_i} and σ_{y_i} are, respectively, the x and y standard deviations for the i th point. The weighted sum of variances in the denominator of equation (15.3.2) can be understood both as the variance in the direction of the smallest χ^2 between each data point and the line with slope b , and also as the variance of the linear combination $y_i - a - bx_i$ of two random variables x_i and y_i .

$$\text{Var}(y_i - a - bx_i) = \text{Var}(y_i) + b^2 \text{Var}(x_i) = \sigma_{y_i}^2 + b^2 \sigma_{x_i}^2 \equiv 1/w_i \quad (15.3.3)$$

The sum of the square of N random variables, each normalized by its variance, is thus χ^2 -distributed.

We want to minimize equation (15.3.2) with respect to a and b . Unfortunately, the occurrence of b in the denominator of equation (15.3.2) makes the resulting equation for the slope $\partial\chi^2/\partial b = 0$ nonlinear. However, the corresponding condition for the intercept, $\partial\chi^2/\partial a = 0$, is still linear and yields

$$a = \left[\sum_i w_i (y_i - bx_i) \right] / \sum_i w_i \quad (15.3.4)$$

where the w_i 's are defined by equation (15.3.3). A reasonable strategy, now, is to use the machinery of Chapter 10 (e.g., the routine *brant*) for minimizing a general one-dimensional function to minimize with respect to b , while using equation (15.3.4) at each stage to ensure that the minimum with respect to a is also minimized with respect to a .

